The accuracy of human population maps for public health application

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Summary

OBJECTIVES Human population totals are used for generating burden of disease estimates at global, continental and national scales to help guide priority setting in international health financing. These exercises should be aware of the accuracy of the demographic information used.

METHODS The analysis presented in this paper tests the accuracy of five large-area, public-domain human population distribution data maps against high spatial resolution population census data enumerated in Kenya in 1999. We illustrate the epidemiological significance, by assessing the impact of using these different human population surfaces in determining populations at risk of various levels of climate suitability for malaria transmission. We also describe how areal weighting, pycnophylactic interpolation and accessibility potential interpolation techniques can be used to generate novel human population distribution surfaces from local census information and evaluate to what accuracy this can be achieved.

RESULTS We demonstrate which human population distribution surface performed best and which population interpolation techniques generated the most accurate bespoke distributions. Despite various levels of modelling complexity, the accuracy achieved by the different surfaces was primarily determined by the spatial resolution of the input population data. The simplest technique of areal weighting performed best.

CONCLUSIONS Differences in estimates of populations at risk of malaria in Kenya of over 1 million persons can be generated by the choice of surface, highlighting the importance of these considerations in deriving per capita health metrics in public health. Despite focussing on Kenya the results of these analyses have general application and are discussed in this wider context.

keywords Kenya, demography, census, areal weighting, pycnophylactic interpolation, dasymetric mapping, smart interpolation

Introduction

Accurate census enumeration combined with information on the spatial distribution of administrative areas is a prerequisite for efficient governance in all nation states (UN 2001). This information, transformed into human population distribution maps, forms an essential population denominator required for many epidemiological studies and for rational public health planning and healthcare provision. Accurate knowledge of human population distribution is needed to define populations at risk of disease for example, to enable exploration of the association of this risk with the environment, poverty and other diseases. It is further necessary to investigate the effectiveness, efficiency and equity of the healthcare system and thus to optimally target and cost interventions through the formal sector (Noor et al. 2003, 2004).

The massive increase in the availability of rasterized (or gridded) imagery of Earth surface conditions, derived primarily from remote sensing, has facilitated a renaissance in the mapping of a range of vector-borne diseases at continental and global scales (Hay 2000; Hay et al. 2000; Randolph 2000; Rogers 2000; Rogers & Randolph 2000; Rogers et al. 2002) and a concomitant improvement in the spatial resolution at which disease risk can be determined. Combinations of these vector-borne disease and demographic data, with assumptions about attributable risk, can be used to generate burden of disease estimates where primary health information system data are wanting (Snow et al. 1998, 1999, 2003, 2005; WHO/UNICEF 2003; Hay et al.
2004, 2005; WHO 2005). The error associated with the population denominator in these calculations is usually ignored.

Similarly, international efforts to quantify the global burdens of a wider range of infectious diseases (Murray & Lopez 1996, 1997; Walker et al. 2002; Williams et al. 2002; Black et al. 2003; Kosek et al. 2003; Morris et al. 2003; de Silva et al. 2003; Zaidi et al. 2004) have traditionally relied on attribution of detailed local information to population data aggregated over large areas; often the national level (Mathers et al. 2003; Murray et al. 2003). Risk is assumed to be equally spatially partitioned among homogenously distributed human populations. It is unlikely that this assumption will be valid for the leading causes of under-five mortality globally; including diarrhoea, pneumonia, malaria (Craig et al. 1999; Hay et al. 2004) and HIV/AIDS (Black et al. 2003; Morris et al. 2003). It is further unlikely that geographical homogeneity is to be found in all of the major underlying risk factors for these causes (Ezzati et al. 2002, 2004), which at the very least will show large urban-rural mortality differentials (Hinrichsen et al. 2002; Dyson 2003; Tatem & Hay 2004; Hay et al. 2005). As techniques for defining disease burdens are moved to sub-national scales to support strategic assessments of progress towards international health and development targets (UNDP 2003), evaluating the fidelity of the associated human population distribution data used will become increasingly important.

Population data is primarily gathered through national census enumeration within country specific administrative boundaries. Methods used to interpolate census polygon data into continuous surfaces are varied and briefly outlined. They include areal weighting, pycnophylactic (mass-preserving) interpolation, dasymetric mapping (density measuring) and various forms of ‘smart’ interpolation (Deichmann 1996; Deichmann et al. 2001) and their use in several public-domain large-area human population distribution maps is also summarized (Table 1, Figure 1).

Areal weighting simply overlays a regular grid (raster surface) on administrative unit (polygon) data and assigns population according to the proportion of the polygon area in the raster grid cell (Mennis 2003). For example, imagine an administrative unit $x$ is a perfect square of $3 \times 3$ km. To turn this into a gridded population map at $1 \times 1$ km spatial resolution, the population of $x/9$ would be assigned to each square in the raster grid. Areal weighting was used to generate the Gridded Population of the World version 2.0 (GPW2.0) (Deichmann et al. 2001) and GPW3.0 (CIESIN/CIAT 2004) and while it has the advantage of simplicity it is confounded by the assumption that human populations distribute themselves uniformly in space.

Pycnophylactic interpolation starts identically to areal weighting and then smooths these raster values iteratively with the weighted average of nearest neighbours; at each iteration the total is adjusted to maintain the population count of the original polygon hence ‘mass-preserving’ (Tobler 1979). The number of nearest neighbours used and iterations applied is subjective and determines the overall level of smoothing required in the output raster surface. Pycnophylactic interpolation is an elegant solution to the problem of generating a continuous surface from discontinuous data and was used to generate GPW 1.0 as part of the Global Demography Project (Tobler et al. 1995, 1997). It unrealistically assumes, however, that no sharp boundaries exist in the distribution of human population (Tobler 1979).

Dasymetric mapping uses ancillary information (often land-use derived from satellite imagery) at higher spatial resolution than the population polygon data to help allocate population (i.e. from forested to urban) who are assumed to differentially inhabit land-use types (Wright 1936; Langford & Unwin 1994; Mennis 2003). Dasymetric mapping again has the merit of relative simplicity and requires little extra data but can be difficult to implement because of the problems of defining the relative weights of the land-use classes. The GPW3.0 with urban-rural

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Coverage</th>
<th>Spatial res. km (deg.)</th>
<th>Population Type</th>
<th>Interpolation method</th>
<th>Admin. units Global/Africa/Kenya</th>
<th>Date</th>
</tr>
</thead>
<tbody>
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<td>Africa</td>
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<td>Residential</td>
<td>Smart In.</td>
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<td>1996</td>
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<tr>
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<td>Residential</td>
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<td>127083/5939/258</td>
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<td>2000</td>
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<td>Residential</td>
<td>Dasy. M.</td>
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<td>2000</td>
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<tr>
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<td>Global</td>
<td>1 (0.5°)</td>
<td>Ambient</td>
<td>Smart In.</td>
<td>69350/5025/258</td>
<td>2002</td>
</tr>
</tbody>
</table>

Areal W., areal weighting; Dasy. M., dasymetric mapping; Smart In., smart interpolation.
reallocation (GPW3.0UR) is an example of dasymetric mapping. GPW3.0UR uses the same global input census data as GPW3.0 but also uses remote sensing [night-time lights (Sutton et al. 2001) and Landsat (Mika 1997)] and other geographic data [Digital Chart of the World (DCW) populated places (Danko 1992)] to define urban extents.

Figure 1 Raster population maps for Kenya. From top left to bottom right: UNEP99, GPW299, GPW399, GPW3UR99, LS99 and AW99 (areal weighted 1999). To compare population data which is highly skewed (Table 4) it is convenient to express values as standard deviations from the mean value for the entire image. The highest values in each image are 3 standard deviations from the mean allowing inter-comparison. Colours and shading are added to accentuate these differences.
Weights are then applied to reallocate urban and rural populations to $1 \times 1$ km grids, based on the census data and published city population data (Balk & Yetman 2004; CIESIN/IFPRI/CIAT 2004). Smart interpolation is technically more sophisticated than dasymetric mapping and uses a wide variety of ancillary data to help disaggregate population polygons as humans are known to distribute themselves non-randomly in the environment (Stewart & Warntz 1958; Langford & Unwin 1994; Cohen & Small 1998). For example, people are more likely to be living near roads and navigable rivers than in lakes or at the top of mountains (Tatem & Hay 2004). Weights can therefore be derived from ancillary data to inform the interpolation process to a raster grid. Smart interpolation tries to incorporate geography explicitly into the population distribution process and can vary in complexity from techniques informed predominantly by transport networks and settlement size, such as the accessibility potential interpolation used in UNEP (Deichmann 1996), to those that use a plethora of ancillary data to define occupation probabilities for all pixels in a raster grid, for example the smart interpolation used in Landscan (Dobson et al. 2000, 2003; Openshaw & Turner 2001).

Uncertainty regarding the derivation of such weights and their geographical homogeneity are the primary complications for the implementation of smart interpolation (Openshaw & Turner 2001). The analyses presented here investigate the accuracy of five public-domain, large-area population surfaces with reference to the 1999 Kenya population and housing census. The performance of areal weighting, pycnophylactic interpolation and accessibility potential interpolation techniques at generating new raster population surfaces for Kenya from the 1999 census data are also investigated, as relevant national agencies and affiliated researchers may have access to higher spatial resolution census data than those used in deriving global raster population surfaces. The resolution of the input census polygon data used in creating large area raster representations of human population distribution is also tested as the spatial resolution of available data is highly variable between countries and has rarely been evaluated outside of high-income nations (Fisher & Langford 1995; Martin 1996; Martin et al. 2000). From the outset we have the reservation that the raster population datasets used were often designed and implemented at global and continental scales and were not necessarily conceived for the applications for which they were tested. This paper is not positioned to favour any implementation or technique but to help evaluate the merits and demerits of these sources of human population distribution data used in epidemiology and public health and thereby help identify priority areas for their refinement. The importance of these considerations in epidemiology is highlighted by quantifying the differences in population at different levels of climate suitability for malaria risk obtained when extracting from the different human population distribution maps available for Kenya.

Materials and methods

The Kenyan Government’s Central Bureau of Statistics implemented a complete population and housing census in 1999 (CBS 2001). It was of the de facto type, so that all persons were enumerated where encountered at the time of census in their homes. Kenya’s administrative unit hierarchy (Figure 2) and population data are available in public-domain to the fifth administrative unit or sub-location (CBS 2001). The number, area (mean, minimum and maximum) and average spatial resolution (ASR; the square root of country area/number of admin units) (Deichmann 1996), of each administrative level are detailed (Table 2).

Public-domain population surfaces

Five public-domain raster datasets of human population distribution for which complete coverages of Kenya could be derived were obtained: UNEP (Deichmann 1996), GPW2.0 (Deichmann et al. 2001), GPW3.0 (Balk & Yetman 2004), GPW3.0UR (Balk & Yetman 2004; CIESIN/IFPRI/CIAT 2004) and LandScan (Dobson et al. 2000, 2003). Hereafter the five human population distribution surfaces are referred to as UNEP99, GPW299, GPW399, GPW3.0UR99 and LS99. The main characteristics of each of these population surfaces are detailed (Table 1) and the surfaces extracted and displayed for Kenya (Figure 1).

The date for which the human population distribution surfaces were generated and their spatial resolution varied so that two further modifications were required to enable inter-comparison. The first was a correction for enumeration year. An estimate of population in 1999 was produced for each raster population distribution using the following equation; $P_{1999} = P_x e^{rt}$ where $P_{1999}$ is the required 1999 population within a pixel, $P_x$ is the population within the same pixel at year $x$, $t$ is the number of years between year $x$ and 1999, and $r$ is the average growth rate (Deichmann 1996). Annual growth rates were determined from provincial intercensal population growth rates (Nairobi 4.8%, Central 1.8%, Coast 3.1%, Eastern 2.1%, North Eastern 9.5%, Nyanza 2.3%, Rift Valley 3.5% and Western 2.5%) (CBS 2001) and applied at the district level to generate population distribution maps for 1999. These changes were implemented with Idrisi Kilimanjaro (Clark Labs, Clark University, Worcester, MA,
The spatial resolution of the administrative boundaries and hence census information was often significantly finer than the spatial resolution of the raster data (Figure 1, Table 2). A second modification was therefore required to increase the spatial resolution of the raster surfaces to $100 \times 100$ m using areal weighting to allow reliable population extractions at the highest order administrative levels. This was particularly important in the urban areas of highest population density. These population surfaces were generated and subsequent extractions performed with ArcView 3.2 (Environmental Systems Research Institute Inc., Redlands, CA, USA).

The co-registration of the raster population and census data was checked by shifting each raster image by one $100 \times 100$ m picture element (pixel) in all orientations (N, W, S, E). In each case the correlation between the human population distribution maps and the census data decreased, showing they were optimally co-registered (aligned); results not shown. The error attributed to using a non-equal-area latitude and longitude reference system for Kenya is minimal as the country straddles the equator and is less than that would be generated by re-sampling the population surfaces to an alternative projection (Bugayevskiy & Snyder 1995). All the population surfaces were therefore analysed in the projection in which they were supplied.

**Population interpolation approaches**

Human population distribution surfaces at $100 \times 100$ m were also independently generated from these census data for Kenya using areal weighting, pycnophylactic
interpolation and accessibility potential interpolation approaches. Each rubric was performed using census data at the national through to sub-location administrative level. Areal weighting was implemented with the zonal attributes extension of ArcView 3.2 (Environmental Systems Research Institute Inc.). Pycnophylactic interpolation was implemented with C code supplied by Uwe Deichmann and a smoothing factor iterated for 100 times or until no further changes in the cell adjustments were observed (Tobler 1979; Tobler et al. 1995). The accessibility potential interpolation technique was also implemented with C code written by and a methodology devised by Uwe Deichmann and Tom Cova (Deichmann 1998). The ancillary data required for accessibility potential interpolation, the human settlement database, river, road, railway networks and gazetted areas and water-bodies were assembled as follows.

Africover data at full spatial resolution (1:100 000) were requested and downloaded (URL: http://www.africover.org). The Africover roads and rivers themes were produced from visual interpretation of digitally enhanced Landsat Thematic Mapper images (bands 4, 3, 2) acquired mainly in 1995. The land-cover classes using the FAO/UNEP international standard land cover classification system (Di Gregorio & Jansen 1998), were similarly derived from visual interpretation of Landsat Thematic Mapper images but using scenes acquired more recently in 1999, the same year as the Kenya national census (CBS 2001). All land-cover polygons classified as an urban area, rural settlement and refugee camp were compared with the sub-location data and aggregated to make them coherent administrative groupings (244 from 327 polygons). For example, the cluster of 12 polygons of urban areas in and around Mombasa were aggregated to one. The centroids of these aggregated polygons were assigned names and population counts using the database of municipalities, town councils and other urban centres from the 1999 population and housing census (CBS 2001) (133 of 244 polygons). Localities that were in the census list but not represented by Africover polygons (n = 144) were added as points using geo-referencing information obtained from Microsoft Encarta 2003 (Microsoft Corporation, Seattle, WA, USA). We were able to locate all of Kenya’s 9 996 991 urban classified population (CBS 2001) in this manner. Finally, we took the population and name of the parent sub-location for all remaining Africover polygons (n = 111) resulting in a total urban associated population of 10 766 874 in 388 localities. The river network was used as supplied by Africover. The newer Africover road network (0.040 km/km² road density for Kenya) was supplemented with the higher density road network supplied with the DCW (Danko 1992) (0.094 km/km² road density for Kenya). A buffer of 600 m around the Africover roads was used to erase duplicate roads in the DCW network and the resulting coverages merged in ArcGIS 8.3 (Environmental Systems Research Institute Inc.) and manually checked and corrected. This resulted in a hybrid road network (0.074 km/km² road density for Kenya) optimizing the more contemporary Africover and more comprehensive DCW. Railway data was used as supplied by DCW as this has not changed since digitization (Danko 1992). Finally, many irregularities were found in the gazetted area polygons for Kenya and their provenance could not be reliably determined. The polygons over land (n = 45) were checked against all ancillary data and manually corrected if their boundaries did not reconcile (i.e. if a gazetted area boundary followed an administrative border, road or river boundary inaccurately it was corrected). These polygons were augmented (n = 21) with all sub-locations that contained National Park, National Reserve or Forest in any of the administrative hierarchy names and had a population density <20 people/km². They were all then classified as gazetted parks (n = 46) or gazetted forests (n = 20).

The road, river and rail layers were merged to create a single transportation network and each component assigned travel speeds as outlined in previous work (Deichmann 1998). The data on settlement size and location were then linked to the transport network by assigning each settlement to the nearest network node. This information was used by the accessibility potential interpolation model to compute a simple accessibility measure.

<table>
<thead>
<tr>
<th>Admin.</th>
<th>n</th>
<th>Mean area</th>
<th>Minimum area</th>
<th>Maximum area</th>
<th>ASR</th>
</tr>
</thead>
<tbody>
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<td>585 055.8</td>
<td>585 055.8</td>
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<td>700.3</td>
<td>182 930.7</td>
<td>270.4</td>
</tr>
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<td>8479.1</td>
<td>231.8</td>
<td>68 229.1</td>
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<td>10.8</td>
<td>20 783.4</td>
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<tr>
<td>Sub-location</td>
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<td>88.3</td>
<td>0.02</td>
<td>10 755.0</td>
<td>9.4</td>
</tr>
</tbody>
</table>

ASR, average spatial resolution = √(country area/number of units) (Deichmann 1996). All units km² save ASR in km.
for each node in the transport network. This measure is the sum of the population of settlements in the vicinity of each node weighted by a function of network distance. The computed accessibility estimates were then interpolated to a 100 m spatial resolution surface. The water body, gazetted forest and gazetted park polygons were, in turn, used to adjust the accessibility surface to 0%, 50% and 20% of their original value (Deichmann 1998). Finally, the sub-location population totals were distributed in proportion to the accessibility index measured for each pixel.

Accuracy assessment and malaria burden implications

Descriptive statistics (Sokal & Rohlf 1997b) for each administrative level were computed from administrative zone totals and accuracy comparisons between census and human population distribution data determined using the population adjusted coefficient of determination (adjusted $r^2$) (Sokal & Rohlf 1997a) and root mean square error (RMSE) (ASPRS 1989). The RMSE is the square root of the mean of the sum of the squares of the error residuals;

$$RMSE = \sqrt{\frac{1}{n-1} \sum (d_i^2)}$$

where $n$ is the number of observations and $d_1$ to $d_n$ the residual values and is essentially a normalized confidence interval on the predicted values. In addition, we derived estimates of the kurtosis and skewness of the census and transformed human population distribution for the areal weighting, pycnophylactic interpolation and accessibility potential interpolation data extractions at each administrative level (Sokal & Rohlf 1997c) to show the influence of the processing on the distribution of the human population distribution data. Kurtosis characterizes the relative ‘peakedness’ or ‘flatness’ of a distribution compared with the normal distribution. ‘Skewness’ is the degree of asymmetry of a distribution around its mean (Sokal & Rohlf 1997c).

The map of climate suitability for malaria transmission (Craig et al. 1999) was partitioned into established classes of malaria risk (Snow et al. 2003) (Figure 3). Populations exposed to different levels of risk were calculated by overlaying the five human population distribution surfaces on a Kenya subset of a map (Figure 3). Populations at risk were also determined directly from the census data by assigning population in direct proportion to the area of each sub-location occupied by a transmission intensity class (i.e. equivalent to areal weighting at sub-location). The results are summarized for the national level (Table 5).

Results

Public-domain population surfaces

The five public-domain raster human population distribution surfaces predicted accurately populations at the provincial (mean adjusted $r^2 = 0.988$, range 0.961–0.999), district (mean adjusted $r^2 = 0.923$, range 0.808–0.998) and divisional levels (mean adjusted $r^2 = 0.803$, range 0.665–0.992) (Table 3, Figure 4). The mean RMSEs, when expressed as a percentage of the mean population size of the administrative level (RMSE%), were correspondingly small at 9.8 (range 7.2–12.6) 19.1 (range 8.9–32.7) and 37.9 (range 11.2–54.7) for province, district and division respectively (Table 3, Figure 4). Moving down the administrative hierarchy, predictive skill decreased; at the location (mean adjusted $r^2 = 0.498$, range 0.212–0.948) and
sub-location (mean adjusted $r^2 = 0.397$, range 0.090–0.904) level (Table 3, Figure 4). The mean RMSE% were higher at 81.3 (range 23.4–111.4) and 107.5 (range 35.6–150.2) for location and sub-location respectively (Table 3, Figure 4).

GPW3UR maintained the lowest RMSE% (35.6) and highest correlation ($r^2 = 0.904$) to the census data at the sub-location level followed by GPW399 (82.5, $r^2 = 0.539$). There was little difference between the poorer performing surfaces, all showing RMSEs larger than the average population size of a sub-location (Table 3, Figure 4). All human population distribution surfaces showed an increase in RMSE with population size of the sub-location and performed badly in sub-locations of very low population (Figure 5).

Population interpolation approaches

The accessibility potential interpolation technique showed more skill at predicting human population
distribution at provincial and district admin levels but performed worse than areal weighting or pycnophylactic interpolation at division, location and sub-location levels (Table 4, Figure 6), although these differences are small, and at sub-location level due principally to the rasterization process. The areal weighting technique was most accurate at the admin 3 level and above. Pycnophylactic interpolation had only cosmetic effects on the human population distribution maps and always decreased accuracy over areal weighting. The population data were highly skewed (Table 4, as people tend to aggregate spatially) but implementing areal weighting, pycnophylactic interpolation and accessibility potential interpolation increased skewness; this effect was most apparent at the divisional level.

The average number of people at risk of malaria in Kenya was 22 808 235 (range 21 439 951–24 070 422) (Table 5). Large discrepancies were also found in each of the classes of categorical risk: the class 2 marginal risk average was 10 033 869 (range 9 390 026–10 429 831), the class 3 acute seasonal transmission risk average was 7 605 795 (range 6 709 852–8 855 830) and the class 4 stable endemic transmission risk average was 5 168 571 (range 4 337 786–5 823 280) (Table 5).

**Discussion**

It should be pointed out that while Kenya has a large diversity in human population distribution from the intensively urban centres of Nairobi and Mombasa to the rural coastal, lakeside and pastoralist communities, the analyses discussed here arise from one country. While illustrative, it is clear that further evaluation of these human population distribution surfaces in countries of different size and experiencing different levels of urbanization and population aggregation are desirable. Nevertheless, as a result of these simple comparisons, certain characteristics that are helpful for evaluating population surfaces for use in epidemiological and public health applications are apparent. All the human population distribution surfaces tested showed a sharp transition in predictive accuracy when evaluated below the level of the input census data regardless of the interpolation method used. This can be seen by examining the number of admin units available for interpolation (Table 1) and the point at which accuracy metrics rapidly decrease (Table 3). UNEP99, GPW299, GPW399, GPW3UR99 and LS99. The graphs show population number (y-axis) by sub-location ordered from lowest to highest population (x-axis). The thick black line are the census counts (CBS 2001). The dots and error bars are the mean and root mean square error, respectively, averaged for sequential blocks of 50 sub-locations for clarity.
the average population of administrative unit at any spatial resolution division finer than the input census data underscores the importance of investigating the local ASR metric (Table 2) no matter how beguiling the spatial resolution of the gridded surface appears (Figure 1) or the sophistication of the modelling used.

It is important to emphasize therefore that knowledge of local resolution of input polygon data is essential when using population surfaces especially when conducting studies at regional, continental and global scales. For example GPW399 has 25 times more population administrative units for Kenya than any of the other surfaces and more administrative units for Africa than LS99 uses for the entire world (Table 1). In addition, all population surfaces will have some countries and regions that will have input data no better than a national average (admin0) and that they may rely on very old census information (URL: http://www.census.gov). The ability to determine the spatial and temporal fidelity of products is therefore highly desirable and the metadata that are distributed with UNEP99 (Deichmann 1996), GPW299 (Deichmann et al. 2001), GPW399 (Balk & Yetman 2004) and GPW3UR99 (Balk et al. 2004; CIESIN/IPFRI/CIAT 2004) may be extremely useful in this regard. Dissemination of such metadata, as well as information including the details of ancillary data used and weights applied in modelling are also prerequisites for interpreting human population distribution surfaces. The information distributed with Landscan, for example, remains limited in this respect. The provision of

### Table 4 Population retrievals and correlation structure between interpolated population sources and administrative level 5 population (n = 6624 in all comparisons)

<table>
<thead>
<tr>
<th>Inter.</th>
<th>Admin.</th>
<th>Total</th>
<th>Mean</th>
<th>Min.</th>
<th>Max.</th>
<th>Kurt.</th>
<th>Skew.</th>
<th>SE</th>
<th>Ad. $r^2$</th>
<th>RMSE</th>
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Inter., interpolation method; Admin., administrative level; AW, areal weighting; PI, pycnophylactic interpolation; API, accessibility potential interpolation; Total, total population; Min., minimum; Max., maximum; Kurt., kurtosis; Skew., skewness; SE, standard error; Ad. $r^2$, adjusted $r$ squared (note all correlations highly significant $P < 0.0001$); RMSE, root mean square error. RMSE %, (RMSE/ Mean) × 100.
details of ancillary data used in such smart interpolation procedures is of importance in avoiding the introduction of bias when these population layers are compared with other information sources based on the same data. Such additional knowledge has never been utilized when deriving burden of disease estimates and part of our future work is directed at using these surfaces to define spatial variation in the confidence of population-based health metrics derived across countries, regions and the globe.

It is clear that the current accuracy of GPW3UR and GPW399 for Kenya is largely due to access to admin5 data. It is also surprising, that despite the difference in complexity between the methods used, and types and ages of data available to generate UNEP99, GPW299 and LS99, the RMSE differences between them are relatively small (Table 3, Figures 4 and 5). Moreover, these differences relate more to how accurately the various maps had defined the national park and forest areas of Kenya in their interpolation processes, than to the techniques used (Figure 5). It is evident therefore that these human population distribution surfaces could be improved simply by using more accurate and contemporary vector files of gazetted locations, although the gains in accuracy due to better ancillary data are insignificant when compared with gains in accuracy due to higher resolution input population data. To a lesser extent the same arguments can be applied to the resolution of the national boundary and coastlines used.

The comparison of simple interpolation techniques through the administrative hierarchy was also illuminating. The accessibility potential interpolation method offered some increased skill at the provincial level but failed to exceed the precision achieved by areal weighting or pycnophylactic interpolation at the lower administrative levels. Pycnophylactic interpolation always decreased accuracy over areal weighting and can thus only be justified on aesthetic grounds. Given the ease of implementation of areal weighting it remains the default technique where the ASR of the population data exceeds that of the ancillary GIS data. The results do point to a role for smart interpolation techniques but that these are going to be strongly influenced by the spatial resolution of the ancillary GIS data used. Smart interpolation procedures are based currently on heuristic rules relating population distribution to socioeconomic factors, without a solid evidence-base for such rules. Finding the balance between the accuracy gained for the increased complexity of smart interpolation, based on reality using high spatial resolution remotely sensed data is the subject of on-going work (Tatem & Hay 2004; Tatem et al. 2004).

The influence of these respective human population surfaces was illustrated dramatically by showing the difference in population at malaria risk for a nation such as Kenya that can be generated simply by the choice of population surface. Differences between the extreme extractions, expressed as a percentage of the average extracted for total population at risk was 10% but reached 28% in the highest endemicity class. Such margins would have very dramatic effects on any disease burden and commodity needs estimation that might use these numbers. It is clear that the assumption of a uniformly distributed human population would generate wildly inaccurate numbers.

We have tested the precision of existing continuous human population distribution surfaces for Kenya and demonstrated the accuracy with which novel human population distribution maps can be generated using a range of available and simple interpolation techniques. The paramount importance of the ASR of the input census data has been highlighted and its consideration when utilizing such data emphasized. Obviously, these

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Class 1 zero risk (Fuzzy climate suitability (FCS = 0), class 2 marginal risk (FCS >0 to <0.25), class 3 acute seasonal transmission (FCS >0.25 to <0.75) and class 4 stable endemic transmission (FCS >0.75). See Figure 3. Source, population data source; UNEP99, United Nations Environment Programme in 1999; GPW299, Gridded Population of the World version 2 in 1999; GPW399, GPWv3.0 in 1999; GPW3UR99, GPWv3.0-UR in 1999; LS99, LandScan in 1999; KPOP99, Kenya census enumeration 1999.
results argue primarily for the free distribution of high
ASR census data globally but in the real world this will
not always be possible. We have therefore further
highlighted the issues involved and accuracy that can be
obtained using simple interpolation techniques at differ-
ent administrative levels where these might be locally
available. However, a corollary to these findings is that
as the ASR of input data for human population
distribution surfaces increases with periodic updates, the
rational for modelling human population distribution
will decrease. The critical importance of metadata and
background information that describes the methodology
data sources used in the construction of the human popu-
lation distribution, that help the local population, was also laboured. Finally, this
is illustrated with the range of population at malaria risk
estimates that can be derived from using these various
public domain human population distribution maps. The
suite of epidemiological application and public health
interventions that use human population distribution
maps should therefore start to be aware of some of the
limitations and opportunities we have documented.

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